From the land to the lab: Studying AI in plant biotechnology

Karacic, Tomislav; Sergeeva, Anastasia V.; Huysman, Marleen

2020

From the land to the lab:

Studying AI in plant biotechnology

Authors:

Tomislav Karacic
Anastasia Sergeeva
Marleen Huysman

Affiliation:

KIN Center for digital innovation, Vrije Universiteit Amsterdam

Contact:

t.karacic@vu.nl
De Boelelaan 1105, HG-5A, 1081 HV Amsterdam, the Netherlands

Introduction

The way AI techniques are implemented and used by professionals are believed to change the way organisations are structured, as well as how the employees of those organisations learn, work, and collaborate (Kellogg, Valentine & Christin 2018; Evetts 2011; Pachidi et al. 2014). Furthermore, introduction of AI can change the way we understand expert knowledge (Faraj et al. 2018) Moreover, digitalisation and AI developments pose a threat to professional authority and autonomy, and there can be a change in power dynamics between professionals (Werr, Noury & Huising 2018) as the expert knowledge used for professional diagnosis and inference making can become embedded in new technologies (Abbott 1988).

We offer a case of the introduction of AI techniques in the interdisciplinary field of plant biotechnology - a field developing techniques for adapting traits in plants such as size, resilience, and shape. Emerging computational techniques afford utilisation of the vast amount of data that can potentially improve efficiency of agricultural production and trait adaptation which seems to be crucial for securing sustainable food production in the wake of climate change and rapid population growth (Trice 2017; Yang et al. 2013; Chawade et al. 2019). Plant biotechnology is a promising case for examining the introduction of AI in work for several reasons. The field is currently intensively implementing AI solutions with an aim of quantitative description of seeds and plants that can make manipulation of them more efficient. Therefore, this case allows us to examine how the work of computer scientists developing AI tools is entering the field of other experts, such as genetic engineers and plant tissue biologists. Moreover, with the further development of AI solutions, plant biotechnology is also likely to have consequences for other types of 'less scientific' work, such as that done by crop farmers. Some scholars speculate that the traditional farming tasks, such as plant breeding experiments, are moving from the field to the lab due to new technological developments (Kloppenburg 2004). Given the emerging social and professional issues caused by digitalisation and use of AI techniques, we find the study of this case to be interesting for the organisation scholars, industry, and policy makers. In this short paper, we outline the background of our research, sketch examples of how AI is used in biotechnology and explain the approach taken in the research. In the full paper, we will provide first empirical evidence from the field.

Plant Biotechnology and the promise of AI

Biotechnology in general is the manipulation of organisms and biological processes to produce useful products. In plant biotechnology specifically, this includes techniques for analysing and changing qualitative (e.g. taste, resilience) and quantitative (e.g. size, weight) traits of cultivated plants (Millam 2007). As a result, practitioners can improve crop yield and quality, or develop disease resistance and abiotic stress tolerance (e.g. tolerance with respect to weather conditions) of seed and plants.

One important technique is polymerase chain reaction (PCR) which enables amplification of small traces of DNA and can be used, for instance, to test plants for pathogens (disease testing) (Surzicky 2000). Here, by cyclical heating and cooling, the two strands of the DNA helix are separated and then recombined in a new order by using an enzymatic reaction amplifying (multiplying) a particular gene. With each thermal cycle, more of the targeted gene is produced. If a plant has even the slightest amount of pathogen DNA on it, PCR will create enough of it for the subsequent test to recognise it.

AI can be used to improve efficiency of that technique. FastFinder PCR Analysis (www.ugentec.com/fastfinder) is a software professionals use for the purposes of PCR data analysis and visualisation. As the algorithms is trained on a great amount of DNA amplification curves (amount of desired genes produced per thermal cycle) across a wide range of different assays (tube samples), FastFinder supports scientists in interpreting the data by automating calculations of the amount of specific gene produced. This can provide information about the uniformity of plants tested for instance, by looking at the uniformity of amplification curves of the same gene across samples. Furthermore, FastFinder affords standardisation across test tubes and increase in time efficiency by making the process operator-independent. Expert intervention is only required in cases of uncertain results which the software flags and asks the operator to mark it as correct or incorrect - further training the algorithm and increasing its future precision. With FastFinder, data interpretation and analysis is taken out from the expert role and embedded in a new technology, a process called commodification of expert knowledge (Abbott 1988).

Except AI commodifying expert knowledge, there are also cases in which it transfers 'less scientific' work into the domain of experts. As an example, consider the GeNee Breeder (www.seed-x.com). GeNee is a machine that tries to predict the genetic traits of a seed from seed's phenotypical appearance (e.g. shape, colour, size), i.e. GeNee incorporates machine vision and a deep learning algorithm to predict what kind of a plant will develop by analysing the visual traits of the seed. To make such a prediction, the seed is placed on a tray that is inserted in the machine that collects visual data of the seed and compares the data to the visual - quality data pairs of the seed it was previously trained on. By predicting the phenotype, breeders can anticipate the size, colour, and taste of plants from a specific seed helping them keeping the quality and uniformity of their products in check.

Traditionally, this kind of experimenting was in the hands of farmers that planted the seed and reported back about the yield and quality of the plants to the biotechnological organisations that provided the seed (Kloppenburg 2004). AI enables biotechnology organisations to do this task by themselves, and in much less time than before, as the GeNee analysis lasts considerably less than the time needed to grow the plants. So, instead of relying on a monotone, 'dirty', scut work (Huising 2015) of farmers, biotech firms can rely on expert work of computer scientists and plant biologists to produce knowledge about the seed quality.

AI is also used in plant breeding. Breeding involves documenting and tracking plant characteristics for ensuring uniform cultivation of crops, as well as detection of pests and diseases. By using cameras, sensors, drones or satellites, breeders can tag and track more characteristics than when done by humans, and rely on machine vision algorithms to derive knowledge from the sensor data, which could improve efficiency and accuracy of their work. Hence, a new skill of digital phenotyping (Yang et al. 2013) - using digital technologies to track phenotypic uniformity or identify issues with crops - becomes an important part of their occupation.

As an example, EnBlightMe project developed a tool for early detection of late blight, a disease that infects potato plants and manifests itself as brown spots (Chawade et al 2019). After collecting images of fields, both affected and unaffected by the disease, with a drone, machine learning technique was used to develop an automatic detection of the disease in its early stages by relying on the visual data coupled with the data about the climate and weather at the point of picture taking. The goal is to rely less on pesticides and farmers constantly examining individual plants, while affording a quick response in the early stages of the disease. Such digital phenotyping tools are an example of introduction of new tasks for professional groups, but also an example of merging of diverse knowledge ranging from engineering and computer science, to climatology and phytopathology (plant disease studies).

Looking at these examples, the use of AI techniques seems to pose threats to the core work of professionals in biotechnology, but also provide opportunities for professionals to expand their jurisdiction on tasks previously performed by farmers. This can initiate tensions among groups that are involved in agricultural production. Given that biotechnology organisations rely on knowledge spanning across biological sciences and chemistry, but also pedology (soil science), agronomy (crop production and soil management), and climate science, as well as engineering and computational sciences, the case we offer to examine concerns highly interdisciplinary tasks were such jurisdictional tensions can become salient, as well as the strategies that groups use to settle them (Kellogg, Valentine & Christin 2018; Christin 2017).

Farmers-Biotech Firms

The relationship between the farmers and the biotechnology firms changed over the years due to technological change (Kloppenburg 2004). Farmers were historically a very independent occupation in terms of the cycle their product goes through. Traditionally, farmers could use seed to produce and sell crops, but also to produce seed for the next harvest, thus being self dependent on the means of their future labour (Kloppenburg 2004). But, with the introduction of high yielding, yet seedless or patented (Harfouche 2012), crops, farmers started cooperating with biotech firms - farmers became dependent on them to acquire higher profitable seed, while the firms relied on farmers to identify which seed had the most desirable traits. With the introduction of AI-based technologies such as the GeNee breeder, this relationship is likely to change, as the firms can rely on their internal expert work to identify high quality seed, while the farmers still depend on them to acquire the seed for their harvest.

In other words, biotech firms can use digital technologies to change their relationship with the farmers. One possible way of doing it is by moving the seed experimentation task from farmers' fields to the internal R&D lab, by transforming farmers' scut work - tedious, monotonous, and instrumental for other, 'more valuable', work (Huising 2015), into expert work through the use of AI.

In sum, research question we are interested in is:
How is the use of AI by biotech firms reconfiguring their relationship with farmers?

Professionals-Management

Biotechnology firms that are implementing AI techniques in their production processes need to be aware of the unintended consequences its use might have. As research repeatedly shows, the vision of a technology and of its implementation by the management can be quite different from its actual everyday use by the practitioners (Christin 2017). Furthermore, in knowledge- intensive settings, management needs to ensure that the organisation goes through a process of appropriation of scientific knowledge if they want to develop an intensive in-house research and development department (Fini et al. 2018; Pisano 2006). Also, management needs to facilitate collaboration between different professionals in interdisciplinary work, as the group needs to overcome differences in understanding, terminology, and expertise (Bruns 2013), especially given the introduction of a new technology (Barrett et al. 2012).

These issues point out that the management needs to foster knowledge integration and expert collaboration if they want the organisation to be successful. But, at least two issues emerge. First, since the promise of AI is in the commodification of some expert knowledge, while to create such tool, organisations need to rely on experts, management finds itself in a difficult situation. Since expert knowledge is a defining feature of experts' profession, and experts themselves are in control of commodification and might resist it, the management needs to find a way to resolve such a *control paradox* (Huising 2014). Second, since introduction of AI to biotechnology brings together two distant groups of experts (biologists and computer scientists) it could be a challenge for them to ensure fruitful collaboration (Bruns 2013) in a situation of changing work, and thus knowledge, practices (Knorr-Cetina 1999).

In the context of dynamics between these two groups, we are interested in answering the question:
What issues does management face in implementing AI in biotechnology?
How does management cope with the control paradox of AI?

Biologists-Engineers

Use of AI in biotechnology further increases the versatility of knowledge needed to perform tasks, in an already highly interdisciplinary field, so the issue of boundary spanning emerges (Aldrich 1977). To illustrate, traditional biologists are driven by the research of nature and accounting for it complexity, while computer scientists operate with decontextualised, abstracted data. Such cross-domain collaborations require cross-domain learning and development of new expertise by the professionals (Bruns 2013). But such development is costly due to cognitive incommensurability of knowledge and the political economy of research (Kaplan, Milde & Cowan 2016). In other words, cross-domain learning requires a lot of cognitive effort and there needs to be enough incentive for it.

Moreover, professionals differ in epistemic cultures - sets of practices they perform to create knowledge (Knorr-Cetina 1999), because their disciplines are governed by different regimes of knowing - practices which guide evaluation of actions and people, and authority arrangements which shape professional jurisdictions (Pachidi et al. forthcoming).

As AI affords performing of new tasks, such as automated disease identification, these tasks can become a subject of jurisdictional conflict (Barrett 2012) between existing professions (biology and computer science), or existing and emerging professions (such as bioinformatics). For instance, due to different epistemological and ontological commitments between groups, there might be a tension with respect to the variables that an algorithm needs to incorporate. In this case, an algorithm is a place where professions can exert their influence to determine their relationship with one another. If that is so, algorithms are a potential place for reshaping of jurisdictional borders between professions. In this context, the research question we are interested in is:
How are work practices in biotechnology being changed with the introduction of AI?

Future Research

We will conduct an ethnographic study at a large biotechnological company specialising in the genetic enhancement of seed. We will take a practice-based perspective in investigating the ways in which the development, implementation and use of AI techniques has consequences for the work of professionals. In doing so, we will pay attention to both the specifics of AI solutions and its development and also take a relational approach, as we want to examine the changes in dynamics between groups on different levels of organisation - among professionals, between professionals and the management, and between the company and the farmers they work with.

The company is a Dutch vegetable breeding and seed enhancement firm. They are one of the leaders in their field worldwide and are investing in development of AI solutions for their production processes. Accordingly, they created a Quantitative Genetics Department which employs AI specialists and experts from biological sciences to develop new tools making them an ideal case for examining professional change in light of new technologies.

We will perform multiple rounds of data collection including in-depth interviews with and non-participant observation of members of the quantitative genetics team, management, and farmers the company cooperates with, and analysis of documents collected in meetings, briefings, and demos. In the full paper, we will provide first findings of the empirical research.

Literature

Abbott, A. (2014). *The system of professions: An essay on the division of expert labor*. University of Chicago press.

Aldrich, H. & Herker, D. (1977). Boundary spanning roles and organization structure. *Academy of Management Review*, 2(2), 217-230.

Barrett, M., Oborn, E., Orlikowski, W.J., & Yates, J. (2012): “Reconfiguring boundary relations: Robotic innovations in pharmacy work.” *Organization Science*, 23 (5), 1448–1466.

Bruns, H. C. (2013). Working alone together: Coordination in collaboration across domains of expertise. *Academy of Management journal*, *56*(1), 62-83.

Chawade, A., van Ham, J., Blomquist, H., Bagge, O., Alexandersson, E., & Ortiz, R. (2019). High-throughput field-phenotyping tools for plant breeding and precision agriculture. *Agronomy*, *9*(5), 258.

Christin, A. (2017). Algorithms in practice: Comparing web journalism and criminal justice. *Big Data & Society*, 4(2), 1-14.

Evetts, J. (2011): “A new professionalism? Challenges and opportunities.” *Current Sociology*, 59 (4), 406–422.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, 28 (1), 62–70.

Fini, R., Rasmussen, E., Siegel, D., & Wiklund, J. (2018). Rethinking the commercialization of public science: From entrepreneurial outcomes to societal impacts. *Academy of Management Perspectives*, *32*(1), 4-20.

Harfouche, A., Meilan, R., Grant, K., & Shier, V. K. (2012). Intellectual property rights of biotechnologically improved plants. In *Plant Biotechnology and Agriculture* (pp. 525-539). Academic Press.

Huising, R. (2015). To hive or to hold? Producing professional authority through scut work. *Administrative Science Quarterly*, 60(2), 263-299.

Huising, R. (2014). The erosion of expert control through censure episodes. *Organization Science*, *25*(6), 1633-1661.

Kaplan, S., Milde, J., & Cowan, R. S. (2017). Symbiont practices in boundary spanning: Bridging the cognitive and political divides in interdisciplinary research. *Academy of Management Journal*, *60*(4), 1387-1414.

Kellogg, K., Valentine, M., & Christin, A. (in print) Algorithms at work: The new contested terrain of control. *Academy of Management Annals, DOI:10.5465/annals.2018. 0174.*

Kloppenburg, J. (2004). *First the seed : the political economy of plant biotechnology* 1492-2000. University of Wisconsin Press.

Knorr-Cetina, K. (1999). *Epistemic cultures: how the sciences make knowledge.* Cambridge, Mass.: Harvard University Press.

Millam, S. (2007). Developments in transgenic biology and the genetic engineering of useful traits. In *Potato biology and biotechnology* (pp. 669-686). Elsevier Science BV.

Pachidi, S., H. Berends, S. Faraj, M. Huysman (forthcoming). Make way for the algorithms: Symbolic actions and change in a regime of knowing, *Organization Science.*

Pachidi, S., Berends, H., Faraj, S., Huysman, M., & van de Weerd, I. (2014). What happens when analytics lands in the organization? Studying epistemologies in clash. In *Academy of management proceedings* (Vol. 2014, No. 1, p. 15590). Briarcliff Manor, NY 10510: Academy of Management.

Pisano, G. (2006). *Science business: The promise, the reality, and the future of biotech*. Harvard Business School Press: Boston, MA.

Trice, R. (2017, Sep 5). Can artificial intelligence help feed the world?. [News article]. Retrieved from https://www.forbes.com/sites/themixingbowl/2017/09/05/can-artificial-intelli-gence-help-feed-the-world/

Weer, A., Noury, L. & Huising, R. (2019, September). Sub-theme 08: [SWG] Digitalization and artificial intelligence: Reshaping professional service firms, professions, and expert work. [Call for papers]. Retrieved from https://www.egosnet.org/jart/prj3/egos/main.jart?rel=de&reserve-mode=active&content-id=1564449184268&subtheme_id=1564449183496

Yang, W., Duan, L., Chen, G., Xiong, L., & Liu, Q. (2013). Plant phenomics and high- throughput phenotyping: accelerating rice functional genomics using multidisciplinary technologies. *Current opinion in plant biology*, 16(2), 180-187.

Surzycki S. (2000). PCR Analysis. In: *Basic Techniques in Molecular Biology*. Springer Lab Manuals. Springer, Berlin, Heidelberg.